

Faster and Stronger: When ANN-SNN Conversion Meets Parallel Spiking Calculation

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Abstract

Spiking Neural Network (SNN), as a brain inspired and energy-efficient network, is currently facing the pivotal challenge of exploring a suitable and efficient learning framework. In this work, we propose a novel parallel conversion learning framework, which establishes a mathematical mapping relationship between each timestep of the parallel spiking neurons and the cumulative spike firing rate. Furthermore, by integrating the above framework with the distribution-aware error calibration technique, we can achieve efficient conversion towards more general activation functions or training-free circumstance.

Theorems

$$oldsymbol{\Lambda}_{ ext{POST}}^l = egin{bmatrix} \mathbf{c}^{l,1} \ \mathbf{c}^{l,2} \ dots \ \mathbf{c}^{l,T} \end{bmatrix} \odot egin{bmatrix} 1 & 0 & \cdots & 0 \ 1 & 1 & \cdots & 0 \ dots & dots & dots \ dots & dots & dots \ 1 & 1 & \cdots & 1 \end{bmatrix}.$$

$$\begin{cases} x \cdot \mathbf{c}^{l,x} \cdot \mathbf{W}^{l} \mathbf{r}^{(l-1),T} = \theta^{l} \\ \mathbf{W}^{l} \mathbf{r}^{(l-1),T} T = (T-x+1)\theta^{l} \end{cases} \Rightarrow \mathbf{c}^{l,x} = \frac{T}{x(T-x+1)}.$$

$$oldsymbol{\Lambda}_{ ext{PC}}^l = oldsymbol{\Lambda}_{ ext{POST}}^l oldsymbol{\Lambda}_{ ext{PRE}}^l = egin{bmatrix} rac{1}{T} & rac{1}{T} & \cdots & rac{1}{T} \ rac{1}{T-1} & rac{1}{T-1} & \cdots & rac{1}{T-1} \ dots & dots & \ddots & dots \ 1 & 1 & \cdots & 1 \end{bmatrix}$$

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Methodology

Table 1: Comparison of various supervised learning methods for SNNs.

Method	Act. Func.	Train. Free	Train. Speed	Train. Mem.	Inf. Lat.	Inf. Speed	Inf. Acc.
STBP Training	Surro. Func.	X	Slow	Large	Ultra Low	Slow	Low
ANN-SNN Conversion	ReLU	X	Fast	Small	Ultra High	Slow	High
AININ-SININ COILVEISIOII	QCFS	X	Fast	Small	Ultra High High Low	Slow	High
Conversion Rect.	QCFS	X	Fast	Small	Low	Slow	High
This Work	QCFS	X	Fast	Small	Ultra Low	Fast	High
THIS WOLK	ReLU	✓	N/A	N/A	Low	Fast	High

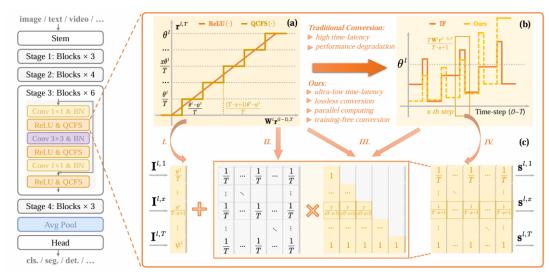


Figure 1: The overall framework of parallel conversion. Here (a) depicts the activation functions in ANNs, (b) shows the sorting property of parallel spiking neurons in the firing phase, and (c) describes the specific process of parallel inference.

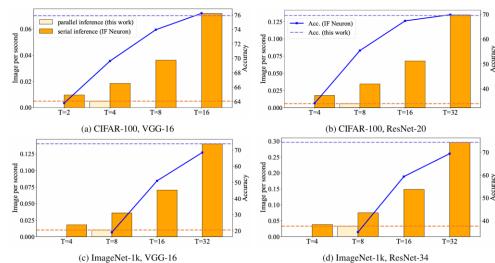
Table 2: Detailed experimental configuration for universal parallel conversion framework.

Conversion Cases	Need Thre. Rec.	Need Calib.	$oldsymbol{\Lambda}_{ ext{PC}}^{l}. ext{shape}$	\mathbf{b}^l .shape	$\theta_{\mathtt{PRE}}^{l}.\mathtt{shape}$	$\theta_{ ext{POST}}^l$.shape
QCFS $(\tilde{T} = T)$	X	X	[T,T]	[T,]	scalar	scalar
QCFS $(\tilde{T} \neq T)$	×	✓	[T,T]	[T, C]	scalar	[C,]
ReLU	✓	✓	[T,T]	[T, C]	[C,]	[C,]

Experiments

Table 3: Comparison of previous state-of-the-art learning methods. † denotes adopting the error calibration technique.

Dataset	Method	Type	ANN Acc.(%)	Arch.	T	SNN Acc.(%)
	OPT	ANN-SNN Conversion	93.51	VGG-16	32	88.79
	QCFS	ANN-SNN Conversion	95.52	93.51	2, 4, 8	91.18, 93.96, 94.95
	SNM	Conversion Rect.	94.09		32	93.43
CIFAR-10	SRP	Conversion Rect.	95.52	VGG-16	32 2, 4, 8 32 6 (4+2) 2, 4 2, 4, 8 6 (4+2) 2, 4, 8 32 6 (4+2) 2, 4 4, 8, 16 6 (4+2) 4, 8 32 32 10 (8+2) 4, 8, 16 4 6 4 8, 16, 32 32 10 (8+2) 4, 8, 16 4	94.47
CITAK-10	Ours	Parallel Conversion	95.43	VGG-16		94.16, 95.50
	QCFS	ANN-SNN Conversion	91.77	ResNet-20	2, 4, 8	73.20, 83.75, 89.55
	SRP	Conversion Rect.	91.77	ResNet-20	32 2, 4, 8 32 6 (4+2) 2, 4 2, 4, 8 6 (4+2) 2, 4, 8 32 6 (4+2) 2, 4 4, 8, 16 6 (4+2) 4, 8 32 32 10 (8+2) 4, 8, 16 4 6 4 8, 16, 32 32 10 (8+2) 4, 8, 16	88.73
	Ours	Parallel Conversion	91.67	ResNet-20	2, 4	87.42, 91.58
	OPT	ANN-SNN Conversion	70.21	VGG-16	32 2, 4, 8 32 6 (4+2) 2, 4 2, 4, 8 6 (4+2) 2, 4, 8 32 6 (4+2) 2, 4 4, 8, 16 6 (4+2) 4, 8 32 32 10 (8+2) 4, 8, 16 4 6 4 8, 16, 32 32 32 10 (8+2) 4, 8, 16 4	56.16
	QCFS	ANN-SNN Conversion	76.28	1 VGG-16 32 2 VGG-16 2, 4, 8 9 VGG-16 32 2 VGG-16 6 (4+2) 3 VGG-16 2, 4, 8 7 ResNet-20 2, 4, 8 7 ResNet-20 6 (4+2) 7 ResNet-20 2, 4, 8 1 VGG-16 32 8 VGG-16 32 8 VGG-16 32 8 VGG-16 32 8 VGG-16 6 (4+2) 1 VGG-16 32 8 VGG-16 32 9 VGG-16 34 1 VGG-16 32 9 VGG-16 32 7 ResNet-20 4, 8, 1 1 VGG-16 32 9 VGG-16 34 8 ResNet-34 6	2, 4, 8	63.79, 69.62, 73.96
	SNM	Conversion Rect.	74.13		32	71.80
CIFAR-100	SRP	Conversion Rect.	76.28	VGG-16	6 (4+2)	74.31
CIFAR-100	Ours	Parallel Conversion	76.11	VGG-16	2, 4	72.71, 75.98
	QCFS	ANN-SNN Conversion	69.94	ResNet-20	4, 8, 16	34.14, 55.37, 67.33
	SRP	Conversion Rect.	69.94	ResNet-20	32 2, 4, 8 32 6 (4+2) 2, 4 2, 4, 8 6 (4+2) 2, 4, 8 32 6 (4+2) 2, 4 4, 8, 16 6 (4+2) 4, 8 32 32 10 (8+2) 4, 8, 16 4 6 4 8, 16, 32 32 4, 8, 16 4 6 4 8, 16, 32 10 (8+2) 4, 8	53.96
	Ours	Parallel Conversion	69.57	ResNet-20		65.31, 69.62
	OPT	ANN-SNN Conversion	72.40	VGG-16	32	54.92
	QCFS	ANN-SNN Conversion	74.29	VGG-16	8, 16, 32	19.12, 50.97, 68.47
	SNM	Conversion Rect.	73.18	VGG-16		64.78
	Burst	Conversion Rect.	74.27	VGG-16	32	70.61
	COS	Conversion Rect.	74.19	VGG-16	10 (8+2)	70.59
	Ours	Parallel Conversion	74.23	VGG-16	4, 8, 16	71.23, 73.92, 74.26
	Ours [†]	Parallel Conversion	74.23	VGG-16	4	71.75
ImageNet-1k	RecDis	STBP Training	-	ResNet-34	32 2, 4, 8 32 6 (4+2) 2, 4 2, 4, 8 6 (4+2) 2, 4, 8 32 2, 4, 8 32 6 (4+2) 2, 4 4, 8, 16 6 (4+2) 4, 8 32 32 32 10 (8+2) 4, 8, 16 6 6 4 4 8, 16, 32 32 10 (8+2) 4, 8, 16 6 4	67.33
imagervet-1k	Dspike	STBP Training	-	ResNet-34	6	68.19
	GLIF	STBP Training	-	ResNet-34	4	67.52
	TAB	STBP Training	-	ResNet-34	4	67.78
	OPT	ANN-SNN Conversion	70.95	ResNet-34	64	59.52
	QCFS	ANN-SNN Conversion	74.32	ResNet-34	8, 16, 32	35.06, 59.35, 69.37
	COS	Conversion Rect.	74.22	ResNet-34		72.66
	Ours	Parallel Conversion	74.30	ResNet-34	4, 8	67.28, 74.32
	Ours [†]	Parallel Conversion	74.30	RecNet-3/	4	72.90





Thanks for Listening!

